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PATENT APPLICATION

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IN THE
UNITED STATES PATENT AND TRADEMARK OFFICE

Inventor(s): Evan R. Kirshenbaum

Confirmation No.:

Application No.: 09/544,751

Examiner: Jones, Hugh M.

Filing Date: 04/07/2000

Group Art Unit: 2128

Title: MODELING DECISION-MAKER PREFERENCES USING EVOLUTION BASED ON SAMPLED PREFERENCES

Mail Stop Appeal Brief-Patents
Commissioner For Patents
PO Box 1450
Alexandria, VA 22313-1450

TRANSMITTAL OF APPEAL BRIEF

Sir:

Transmitted herewith is the Appeal Brief in this application with respect to the Notice of Appeal filed on 03/25/2005.

The fee for filing this Appeal Brief is (37 CFR 1.17(c)) $500.00.

(complete (a) or (b) as applicable)

The proceedings herein are for a patent application and the provisions of 37 CFR 1.136(a) apply.

( ) (a) Applicant petitions for an extension of time under 37 CFR 1.136 (fees: 37 CFR 1.17(a)-(d) for the total number of months checked below:

( )	one month	$120.00
( )	two months	$450.00
( )	three months	$1020.00
( )	four months	$1590.00

( ) The extension fee has already been filled in this application.

(X) (b) Applicant believes that no extension of time is required. However, this conditional petition is being made to provide for the possibility that applicant has inadvertently overlooked the need for a petition and fee for extension of time.

Please charge to Deposit Account **08-2025** the sum of **$500.00**. At any time during the pendency of this application, please charge any fees required or credit any over payment to Deposit Account 08-2025 pursuant to 37 CFR 1.25. Additionally please charge any fees to Deposit Account 08-2025 under 37 CFR 1.16 through 1.21 inclusive, and any other sections in Title 37 of the Code of Federal Regulations that may regulate fees. A duplicate copy of this sheet is enclosed.

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Typed Name: **Kerri Hyland**

Signature: Kerri Hyland

Respectfully submitted,

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Rev 12/04 (Aplbrief)

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

In re Application of: Evan R. Kirshenbaum	§	Group Art Unit: 2128
Serial No.: 09/544,751	§	Examiner: Jones, Hugh M.
Filed: April 7, 2000	§	
For: MODELING DECISION-MAKER PREFERENCES USING EVOLUTION BASED ON SAMPLED PREFERENCES	§	Atty. Docket: 10990719-1 NUHP:0287/BLT/POW

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CERTIFICATE OF MAILING
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May 25, 2005 — Kerri Hyland
Date — Kerri Hyland

APPEAL BRIEF PURSUANT TO 37 C.F.R. §§ 41.31 AND 41.37

This Appeal Brief is being filed in furtherance to the Notice of Appeal mailed on March 22, 2005, and received by the Patent Office on March 25, 2005.

The Commissioner is authorized to charge the requisite fee of $500.00, and any additional fees which may be necessary to advance prosecution of the present application, to Account No. 08-2025, Order No. 10990719-1/BLT/POW (NUHP:0287).

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1. REAL PARTY IN INTEREST

The real party in interest is Hewlett-Packard Development Company, L.P., a Texas Limited Partnership having its principal place of business in Houston, Texas and the Assignee of the above-referenced application. The Assignee of the above-referenced application will be directly affected by the Board's decision in the pending appeal.

2. RELATED APPEALS AND INTERFERENCES

Appellant is unaware of any other appeals or interferences related to this Appeal. The undersigned is Appellant's legal representative in this Appeal.

3. STATUS OF CLAIMS

Claims 1-38 are currently pending. Further, claims 1-38 are currently under final rejection and are thus the subject of this appeal.

4. STATUS OF AMENDMENTS

The instant claims have not been amended subsequent to the final rejection. Accordingly, there are no outstanding amendments to be considered by the Board.

5. SUMMARY OF CLAIMED SUBJECT MATTER

The present invention generally relates to modeling the preferences of a decision-maker using sampled pair-wise preferences. *See* Application, page 3, lines 3-5. A preference model obtained in accordance with one embodiment of the present invention may be used in a variety of systems to provide choices among available alternatives based on what a decision-maker (e.g., human or web agent) is likely to select. *See* Application, page 3, lines 20-24; *see also* page 6, line 32-page 7, line 6. Indeed, once generated, a preference model

may be used to determine or predict the preferences of a decision-maker or group of decision-makers with respect to a combination of available alternatives. *See* Application, page 6, lines 20-26. For example, predicted preferences may be used to determine appropriate products, services, web page and/or web site designs, store front designs, store shelf arrangements, facility site selections, foods, food types, movies, plays, music, and so forth to display for selection by a particular decision-maker or target audience. *See* Application, page 7, lines 7-29; *see also* page 14, lines 25-31.

With regard to aspects of the invention set forth in independent claim 1, discussions of the recited features of claim 1 can be found at least in the locations in the specification and drawings cited below. By way of example, an embodiment in accordance with the present invention relates to a method for generating a model of preferences (e.g., 12) of a decision-maker (e.g., 14, 18). *See, e.g.,* Application, Figs. 2-4; *see also* Figs. 5a-5c. The method comprises the step of identifying a set of alternatives (e.g., 20, 21, 22) to be presented to the decision-maker (e.g., 14, 18). *See, e.g.,* Application, Fig. 2, block 70; *see also* Fig. 1; *see also* page 7, lines 17-29. The method also comprises the step of identifying a set of attributes (e.g., 30, 31, 32, 40, 41, 42, 50, 51, 52) associated with the alternatives. *See, e.g.,* Application, Fig. 2, block 72; *see also* Fig. 1; *see also* page 7, line 31-page 8, line 7. The method also comprises the step of characterizing the alternatives by obtaining a set of values (e.g., v1, v2, v3, v4, v5, v6, v7, v8, v9) for the attributes of each alternative. *See, e.g.,* Application, Fig. 2, block 74; *see also* Fig. 1; *see also* page 8, lines 9-21. The method also comprises the step of obtaining a sample set of pair-wise preferences (e.g., B>C, A>C, B>A) among a subset of the alternatives. *See, e.g.,* Application, Fig. 2, block 76; *see also* page 8, line 23-page 9, line 31. The method also comprises the step of evolving the model of preferences that is stored in memory by iteratively generating a set of candidate models (e.g.,

100, 110, 120) and evaluating the candidate models using a fitness measure which is based on the sample set of pair-wise preferences. *See, e.g.*, Application, Fig. 2, block 78; *see also* Figs. 3 and 4; *see also* page 9, line 33-page 12, line 10.

With regard to aspects of the invention set forth in independent claim 21, discussions of the recited features of claim 21 can be found at least in the locations in the specification and drawings cited below. By way of example, an embodiment in accordance with the present invention relates to a system (e.g., 10) for designing a presentation (e.g., web page, advertisement, direct-marketing solicitation) comprising means (e.g., 16)(e.g., computer program, web-based service, device with processing resources) for selecting between a set of available alternatives (e.g., 20, 21, 22) each characterized by a set of observable attributes (e.g., 30, 31, 32, 40, 41, 42, 50, 51, 52) using a model of preferences of a target audience (e.g., 12) wherein the model that is stored in memory is evolved by iteratively generating a set of candidate models (e.g., 100, 110, 120) and evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences (e.g., B>C, A>C, B>A) based upon responses from the target audience to a series of questions. *See, e.g.*, Application, Fig. 1; *see also* page 14, line 26-page 17, line 28.

With regard to aspects of the invention set forth in independent claim 26, discussions of the recited features of claim 26 can be found at least in the locations in the specification and drawings cited below. By way of example, an embodiment in accordance with the present invention relates to a device (e.g., 10, 16)(e.g., presentation system, product support system, software distribution system, web server, physical device) for deciding among a set of alternatives (e.g., 20, 21, 22) each characterized by a set of observable attributes (e.g., 30, 31, 32, 40, 41, 42, 50, 51, 52) comprising means (e.g., 10, 16) for storing a preference model

(e.g., 12) constructed by iteratively generating a set of candidate models (e.g., 100, 110, 120) and evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences (e.g., B>C, A>C, B>A) that are stored in memory. *See, e.g.,* Application, Fig. 1; *see also* page 16, line 24-page 17, line 28; *see also* page 3, lines 20-31.

With regard to aspects of the invention set forth in independent claim 33, discussions of the recited features of claim 33 can be found at least in the locations in the specification and drawings cited below. By way of example, an embodiment in accordance with the present invention relates to a method of customizing a computer program, the method comprising the acts of presenting a user (e.g., 14, 18) with a plurality of pairs of customization options (e.g., 20, 21, 22) through a series of questions. *See, e.g.,* Application, page 15, line 32-page 16, line 22; *see also* Fig. 2, block 70; *see also* Figs. 3-5. The method also comprises the step of generating the user's preferences for each pair of options in the plurality in response to the user's answers to the series of questions. *See, e.g.,* Application, Fig. 2, block 72; *see also* page 7, line 31-page 8, line 7. The method also comprises the step of assigning a plurality of values (e.g., v1, v2, v3, v4, v5, v6, v7, v8, v9) to each element of each pair of options in the plurality. *See, e.g.,* Application, Fig. 2, blocks 74 and 76; *see also* Fig. 1; *see also* page 8, line 9-page 9, line 31. The method also comprises evaluating a fitness measure for each of the plurality of values. *See, e.g.,* Application, Fig. 2, block 78; *see also* Figs. 3 and 4; *see also* page 9, line 33-page 12, line 10. The method also comprises selecting a subset from the plurality of values, wherein each member of the subset exceeds the fitness measure. *See, e.g.,* Application, Fig. 4, block 90; *see also* page 12, lines 12-25. The method also comprises combining the members of the subset using genetic operations to produce new values for each element of each pair of options in the plurality. *See, e.g.,* Application, Fig. 4, block 92; *see also* page 12, lines 12-25.

6. GROUNDS OF REJECTION TO BE REVIEWED ON APPEAL

First Ground of Rejection for Review on Appeal:

Appellant respectfully urges the Board to review and reverse the Examiner's first ground of rejection in which the Examiner rejected claims 1-38 under 35 U.S.C. § 101 as being an abstract idea that is not tied to a technological art, environment or machine which would result in a practical application producing a concrete, useful, and tangible result.

Second Ground of Rejection for Review on Appeal:

Appellant respectfully urges the Board to review and reverse the Examiner's second ground of rejection in which the Examiner rejected claim 6 under 35 U.S.C. § 112, first paragraph, as failing to comply with the enablement requirement.

Third Ground of Rejection for Review on Appeal:

Appellant respectfully urges the Board to review and reverse the Examiner's third ground of rejection in which the Examiner rejected claims 1-24, 26-29, 31, and 31-38 under 35 U.S.C. § 102(b) as being anticipated by Nomura et al. (U.S. Patent No. 5,740,323), which is referred to hereinafter as "the Nomura reference."

Fourth Ground of Rejection for Review on Appeal:

Appellant respectfully urges the Board to review and reverse the Examiner's fourth ground of rejection in which the Examiner rejected claims 1-38 under 35 U.S.C. § 102(b) as being clearly anticipated by Terano et al., *Marketing Data Analysis Using Inductive Learning and Genetic Algorithms with Interactive-and Automated-Phases*, IEEE Int. Conf. Evolutionary Computation, 771 (1995), which is referenced hereinafter as "the Terano

reference." A copy of the Terano reference is included as Exhibit A in the Appendix of Evidence.

Fifth Ground of Rejection for Review on Appeal:

Appellant respectfully urges the Board to review and reverse the Examiner's fifth ground of rejection in which the Examiner rejected claims 1-24, 26-29, 31, and 33-38 under 35 U.S.C. § 102(e) as being anticipated by Martinka et al. (U.S. Patent No. 6,591,257), which is referred to hereinafter as "the Martinka reference."

Sixth Ground of Rejection for Review on Appeal:

Appellant respectfully urges the Board to review and reverse the Examiner's sixth ground of rejection in which the Examiner rejected claims 25, 30, and 32 under 35 U.S.C. § 103(a) as being obvious over the Nomura reference in view of the Terano reference and in further view of alleged admissions by the Appellant.

7. ARGUMENT

As discussed in detail below, the Examiner has improperly rejected the pending claims. Further, the Examiner has misapplied long-standing and binding legal precedents and principles in rejecting the claims under Sections 101, 102 and 103. Accordingly, Appellant respectfully requests full and favorable consideration by the Board, as Appellant contends that claims 1-38 are currently in condition for allowance.

A. Ground of Rejection No. 1:

The Examiner rejected claims 1-38 under 35 U.S.C. § 101 as being an abstract idea that is not tied to a technological art, environment or machine which would result in a practical application producing a concrete, useful, and tangible result. The Appellant

respectfully disagrees with the reasoning used by the Examiner in support of the § 101 rejection. Furthermore, the Appellant respectfully traverses the § 101 rejection because the pending claims are directed to statutory subject matter.

i. <u>Failure to fall within the technological arts is NOT a basis for a § 101 rejection.</u>

The Appellant respectfully asserts that the Examiner's assertion that patentable subject matter must fall within the "technological arts" is unfounded. Although there is no legal authority cited by the Examiner in support of the "technological arts" argument, this rejection was first enunciated in *In re Musgrave*, 431 F.2d 882, 893, 167 U.S.P.Q. 280, 289 (C.C.P.A. 1970) (holding that all that is necessary to make a sequence of operational steps a statutory "process" within 35 U.S.C. § 101 is that it be in the technological arts); *see also In re Benson*, 441 F.2d 682, 688, 169 U.S.P.Q. 548 (C.C.P.A. 1971) (holding that computers were within the technological arts and thus were statutory subject matter). Furthermore, the Court of Claims and Patent Appeals, in reviewing the language of *In re Musgrave*, *In re Benson*, and *Gottschalk v. Benson*, rejected the notion that the "technological arts" rejection created or formed a basis for a § 101 rejection. *See In re Toma*, 197 U.S.P.Q. 852 (C.C.P.A. 1978). That is, a "technological arts" rejection was not intended to create a generalized definition of statutory subject matter. *See id.* at 857. Accordingly, the Appellant respectfully asserts that there is no "technological arts" definition of statutory subject matter. Thus, the Examiner's rejection under Section 101 that the Appellant's claims are not directed to statutory subject matter because they do not fall within the "technological arts" is erroneous and should be reversed.

ii. The present claims are directed to statutory subject matter.

Any analysis of whether a claim is directed to statutory subject matter begins with the language of 35 U.S.C. § 101, which reads:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

In interpreting this section, the Supreme Court stated that Congress intended statutory subject matter to "include *anything* under the sun that is made by man." *Diamond v. Chakrabarty*, 447 U.S. 303, 309, 206 U.S.P.Q. 193, 197 (1980) (emphasis added). Although this statement may appear limitless, the Supreme Court has identified three categories of unpatentable subject matter: laws of nature, natural phenomena, and abstract ideas. *See, Diamond v. Diehr*, 450 U.S. 175, 182, 209 U.S.P.Q. 1, 7 (1981). Accordingly, so long as a claim is not directed to one of the three specific areas listed above, the claim is directed to patentable subject matter. Thus, it is improper to read Section 101 to embrace additional categories of excluded subject matter where the legislative history does not indicate that Congress clearly intended such limitations to exist. *In re Alappat*, 31 U.S.P.Q.2d 1545, 1556 (Fed. Cir. 1994) (citing *Chakrabarty* 447 U.S. at 308).

The fact that a claim includes or is directed to an algorithm is not grounds for holding that the claim is directed to non-statutory subject matter. *See, In re Iwashashi*, 12 U.S.P.Q.2d 1908, 1911 (Fed. Cir 1989). Rather, the proscription against patenting an algorithm, to the extent it still exists, is narrowly limited to *mathematical algorithms in the abstract*, e.g., describing a mathematical algorithm as a procedure for solving a given type of mathematical problem. *See, AT&T Corp. v. Excel Communications, Inc.*, 50 U.S.P.Q.2d 1447, 1450 (Fed. Cir 1999). Indeed, the courts are aware that any step-by-step process, be it electronic,

chemical, or mechanical, involves an algorithm. *Id.* at 1450. For example, claims drawn to a long-distance telephone billing process containing mathematical algorithms were held patentable because the process used the algorithm to produce a useful, concrete, tangible result without preempting other uses of the mathematical principle. *Id.* at 1452.

Thus, inquiry into what is statutory subject matter simply requires "an examination of the contested claims to see if the claimed subject matter as a whole is a disembodied mathematical concept representing nothing more than a 'law of nature' or an 'abstract idea, or if the mathematical concept has been reduced to some practical application rendering it 'useful'." *Id.* at 1451 (citing and quoting *In re Alappat*, 31 U.S.P.Q.2d at 1557). Furthermore, a Section 101 analysis "demands that the focus in any statutory subject matter analysis be on the *claim as a whole*." *In re Alappat*, 31 U.S.P.Q.2d at 1557 (citing *Diehr*, 450 U.S. at 192) (emphasis in original). Indeed, the dispositive inquiry is whether the claim *as a whole* is directed to statutory subject matter, it is irrelevant that a claim may contain, as part of the whole, subject matter that would not be patentable by itself. *Id.*

Independent claim 1, for example recites the following:

> A method for generating a model of preferences of a decision-maker, comprising the steps of:
> identifying a set of alternatives to be presented to the decision-maker;
> Identifying a set of attributes associated with the alternatives;
> characterizing the alternatives by obtaining a set of values for the attributes of each alternative;
> obtaining a sample set of pair-wise preferences among a subset of the alternatives;
> evolving the model of preferences that is stored in memory by iteratively generating a set of candidate models and evaluating the candidate models using a fitness measure

> which is based on the sample set of pair-wise preferences.

Appellant respectfully asserts that methods, systems, and devices for generating and evolving preference models, as set forth in the present application, are clearly useful for solving problems relating to tradeoffs between consumer preferences. *See, e.g.,* Application, page 1, lines 9-18. For example, generating a preference model can provide a useful tool that benefits decision makers (e.g., human beings) and option providers (e.g., suppliers) in fields relating to e-commerce, product support systems, software distribution, and web servers,. *See* Application, page 3, lines 4-32; page 6, line 27 to page 7, line 29; page 17, lines 8-19. Clearly, a person of ordinary skill in the art in the field of advertising, marketing, or web design would find preference models "useful" to effectively advertise, market, and design their products. Accordingly, the Appellant respectfully submits that the pending claims are directed to statutory subject matter, and respectfully requests that the Board overturn the rejection and allow the pending claims.

B. **Ground of Rejection No. 2:**

The Examiner rejected claim 6 under 35 U.S.C. § 112, first paragraph, as failing to comply with the enablement requirement. Specifically, the Examiner stated the following:

> In particular, the claim recites computer program type, mathematical expression type, neural network type and belief network type. Such features are not supported in the specification in such a way as to enable one skilled in the art to which it pertains, or with which it is most nearly connected, to make and/or use the invention.
>
> Final Office Action, page 5.

Additionally, in the Response to Arguments, the Examiner stated the following:

> [T]he only mention, in the specification, of neural networks and belief networks, is a single sentence (lines 20-22, page 10, specification). There is no

> disclosure of how to apply these technologically complex concepts to the claimed invention.
>
> Final Office Action, page 14.

Appellant respectfully traverses the § 112 rejection. The test for enablement is set forth in M.P.E.P. § 2164.01. From that section, the test for enablement appears to be whether one skilled in the art could make or use the invention from the disclosure in the patent coupled with information known in the art *without undue experimentation*. *See Mineral Separation v. Hyde,* 242 U.S. 261, 270 (1916). In order to make an appropriate rejection, the Examiner has the initial burden to establish a reasonable basis to question the enablement provided for the claimed invention. M.P.E.P. § 2164.04. Thus, the Examiner's rejection should provide factors, reasons, and evidence that lead the Examiner to conclude that the specification fails to teach how to make and use the claimed invention without undue experimentation. *Id.* Further, detailed procedures for making and using the invention may not be necessary if the description of the invention itself is sufficient to permit those skilled in the art to make and use the invention.

The assertions by the Examiner do not satisfy the evidentiary requirements set forth in M.P.E.P. § 2164 and the legal precedents cited above. Indeed, the Examiner merely stated that claim 6 recites subject matter that is not described in such a way as to enable one skilled in the art to make and/or use the invention. While the Examiner attempted to support this assertion by stating that there is no disclosure of how to apply neural networks and belief networks to the claimed invention, the Examiner has not provided factors, reasons, and evidence to support the Examiner's assertion that the specification fails to teach how to make and use the claimed invention without undue experimentation.

Appellant asserts that one of ordinary skill in the art would recognize the recited technological concepts and would be enabled to utilize these concepts in the context of embodiments of the present invention. In fact, contrary to the Examiner's assertions, candidate models in the present application are clearly described throughout the specification to enable one skilled in the art to make or use the invention. Specifically, passages on page 10, line 5 to page 14, line 24 describe exemplary embodiments of such models. These models are even described to include computer programs, mathematical expressions, neural networks, and belief networks. *See* Application, page 10, lines 15-22. Further, neural networks and belief networks are well defined and known to those of ordinary skill in the art, as respectively evidenced by Exhibits B and C in the Appendix of Evidence. A neural network may include an interconnected group of artificial or biological neurons. *See* Wikipedia, Neural Network *at http:/en.wikipedia.org/wiki/Neural_network* (Exhibit B). A belief network may include a Bayesian belief network, which may be defined as "a directed acyclic graph of nodes representing variables and arcs representing dependence relations among variables." *See* Wikipedia, Bayesian Network *at http:/en.wikipedia.org/wiki/Belief_network* (Exhibit C).

The Examiner clearly has not met the burden of establishing a reasonable basis to question the enablement provided for the claimed subject matter. As such, the Appellant respectfully submits that claim 6 is clearly enabled in the present application. Accordingly, the Appellant respectfully requests that the Board overturn the rejection and allow claim 6.

C. Ground of Rejection No. 3:

The Examiner rejected claims 1-24, 26-29, 31, and 31-38 under 35 U.S.C. § 102(b) as being anticipated by the Nomura reference. Appellant respectfully traverses this rejection. Each of the independent claims is separately addressed below.

i. Judicial precedent has clearly established a legal standard for a prima facie anticipation rejection.

Anticipation under Section 102 can be found only if a single reference shows exactly what is claimed. *Titanium Metals Corp. v. Banner*, 227 U.S.P.Q. 773 (Fed. Cir. 1985). Thus, for a prior art reference to anticipate under Section 102, every element of the claimed invention must be identically shown in a single reference. *In re Bond*, 15 U.S.P.Q.2d 1566 (Fed. Cir. 1990). Moreover, the prior art reference also must show the *identical* invention "*in as complete detail as contained in the ... claim*" to support a *prima facie* case of anticipation. *Richardson v. Suzuki Motor Co.*, 9 U.S.P.Q. 2d 1913, 1920 (Fed. Cir. 1989) (emphasis added). Accordingly, Appellant needs only point to a single element not found in the cited reference to demonstrate that the cited reference fails to anticipate the claimed subject matter.

ii. The Examiner's rejection is improper because the rejection fails to establish a prima facie case of anticipation.

On a preliminary note, Appellant asserts that the Examiner failed to provide clear explanations of all rejections, as required by 37 C.F.R. § 1.104 and M.P.E.P. § 707.07. For example, the Examiner appears to base his rejection on a mischaracterization of aspects of the present claims as "mere decision making." *See* Final Office Action, page 14. This is not useful in aiding the applicant to judge the propriety of continuing the prosecution. *See* 37 C.F.R. § 1.104(a)(2).

In the present case, Nomura does not anticipate the pending claims because the Nomura reference fails to disclose all of the claimed subject matter. For example, independent claim 1 recites "obtaining a sample set of pair-wise preferences among a subset of the alternatives" and "evaluating the candidate models using a fitness measure which is based on the sample set of pair-wise preferences." Independent claim 21 recites "using a model of preferences of a target audience wherein the model that is stored in memory is evolved by iteratively generating a set of candidate models and evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences." Independent claim 26 recites "evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences that are stored in memory." Independent claim 33 recites "generating the user's preferences for each pair of options in the plurality in response to the user's answers to the series of questions" and "evaluating a fitness measure for each of the plurality of values."

In contrast, the Nomura reference merely discloses an inference knowledge extracting apparatus capable of being adapted to a change of input/output data. The knowledge extracting apparatus performs evolutionary adaptation by way of input/output data. *See* Normura, col. 2, lines 48-57. The evolutionary adaptation type inference knowledge extracting apparatus 1 includes a fuzzy rule extracting section 4. *See* Normura, col. 7, lines 42-47. The apparatus selects individuals based on the degree of fitness that is calculated for each individual. *See* Normura, col. 7, lines 48-67. Clearly, the Nomura reference does not teach or suggest obtaining a sample set of pair-wise preferences among a subset of the alternatives, much less evaluating the models using a fitness measure which is based on the sample set of pair-wise preferences. Thus, the Nomura reference clearly does not disclose or suggest obtaining or utilizing pair-wise preferences, as recited in the present claims.

For at least the reasons set forth above, the Appellant respectfully submits that independent claims 1, 21, 26, and 33 and the respective dependent claims are not anticipated by the Nomura reference. Accordingly, Appellant requests that the Board overturn the rejection based on the Nomura reference and allow claims 1-24, 26-29, 31, and 31-38.

D. Ground of Rejection No. 4:

The Examiner rejected claims 1-38 under 35 U.S.C. § 102(b) as being clearly anticipated by the Terano reference. Appellant respectfully traverses this rejection. Each of the independent claims is separately addressed below.

i. The Examiner's rejection is improper because the rejection fails to establish a prima facie case of anticipation.

On a preliminary note, Appellant asserts that the Examiner failed to provide clear explanations of all rejections, as required by 37 C.F.R. § 1.104 and M.P.E.P. § 707.07. For example, the Examiner appears to base his rejection on a mischaracterization of aspects of the present claims as "mere decision making." *See* Final Office Action, page 14. This is not useful in aiding the applicant to judge the propriety of continuing the prosecution. *See* 37 C.F.R. § 1.104(a)(2).

The Terano reference does not anticipate the pending claims because the Terano reference fails to disclose all of the claimed subject matter in the independent claims 1, 21, 26, and 33. For example, independent claim 1 recites "obtaining a sample set of pair-wise preferences among a subset of the alternatives" and "evaluating the candidate models using a fitness measure which is based on the sample set of pair-wise preferences." Independent claim 21 recites "using a model of preferences of a target audience wherein the model that is stored in memory is evolved by iteratively generating a set of candidate models and

evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences." Independent claim 26 recites "evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences that are stored in memory." Independent claim 33 recites "generating the user's preferences for each pair of options in the plurality in response to the user's answers to the series of questions" and "evaluating a fitness measure for each of the plurality of values."

In contrast to the claimed subject matter, the Terano reference merely discloses a method of assisting marketing decision makers in interpreting noisy questionnaire data. *See* Terano, Introduction. The reference utilizes an interactive phase to evaluate decision trees and an automated phase to develop offspring. *See id.* The interactive phase generates sets of decision trees with selected features. *See* Terano, Algorithm for Acquiring Decision Rules. Then, a domain expert selects two "good" decision trees or two "good" rules. *See id.* As a result, the Terano reference does not teach or suggest obtaining a sample set of pair-wise preferences among a subset of the alternatives, much less evaluating the models using a fitness measure which is based on the sample set of pair-wise preferences. Rather, the Terano reference describes that the domain expert selects two rules from a set of rules or two decision trees from a set of decision trees. *See* Terano, Algorithm for Acquiring Decision Rules. Nothing in the reference discloses or suggests obtaining pair-wise preferences or using the pair-wise preferences to evaluate the candidate models. Thus, the Terano reference clearly does not disclose or suggest the claimed subject matter.

For at least the reasons set forth above, the Appellant respectfully submits that independent claims 1, 21, 26, and 33 and the respective dependent claims are not anticipated

by the Terano reference. Accordingly, Appellant requests that the Board overturn the rejection based on the Nomura reference and allow claims 1-24, 26-29, 31, and 31-38.

E. **Ground of Rejection No. 5:**

The Examiner rejected claims 1-24, 26-29, 31, and 33-38 under 35 U.S.C. § 102(e) as being clearly anticipated by the Martinka reference. Appellant respectfully traverses this rejection. Each of the independent claims is separately addressed below.

i. **The Examiner's rejection is improper because the rejection fails to establish a prima facie case of anticipation.**

On a preliminary note, Appellant asserts that the Examiner failed to provide clear explanations of all rejections, as required by 37 C.F.R. § 1.104 and M.P.E.P. § 707.07. For example, the Examiner appears to base his rejection on a mischaracterization of aspects of the present claims as "mere decision making." *See* Final Office Action, page 15. This is not useful in aiding the applicant to judge the propriety of continuing the prosecution. *See* 37 C.F.R. § 1.104(a)(2). Additionally, the Appellant notes that the Examiner has essentially paraphrased the abstract from the Normura reference, which is not the art being cited in this rejection, as the basis for the rejection. Specifically, the Normura abstract recites:

> There is provided an inference knowledge extracting apparatus capable of being adapted to a change of input/output data. In a fuzzy rule individual group storing section is stored a group of individuals having a gene string associated with a fuzzy rule of a fuzzy rule storing section by a fuzzy rule gene associating section. A fuzzy rule individual selecting section stochastically selects individuals having a small output error with respect to the input/output data based on a calculation result of fitness obtained by an individual fitness calculating section. A fuzzy rule individual gene manipulating section executes a gene manipulating operation on each individual selected by the individual fitness calculating section. The fuzzy rule gene associating section, individual fitness calculating section, fuzzy rule individual selecting section, fuzzy rule individual gene manipulating section and a rule weight

> deciding section are functioned, thereby executing an evolutionary adaptation operation to extract a fuzzy rule that is evolutionarily adapted to the change of the input/output data.
>
> Normura et al., abstract.

Further, the Examiner has simply cited to multiple columns of the Martinka reference without any specific citations within the reference. The Appellant believes that these citations are entirely inadequate to fulfill the Examiner's obligations under 37. C.F.R. § 1.104(c)(2), which requires the Examiner to designate as nearly as practicable the particular part of the reference relied upon by the Examiner. Indeed, the Examiner is required to state the reasons for any adverse action or any objection. *See* 37 C.F.R. § 1.104(c)(2). Further, "[w]hen such prior art is cited, its pertinence should be explained." M.P.E.P. 707.05; *see* 37 C.F.R. § 1.104(c)(2). As such, the Appellant believes the rejection provided by the Examiner to be deficient on its face.

Nevertheless, the Appellant has attempted to ascertain which, if any, portions of the Martinka reference may be relevant to formulate a response. However, after reviewing the entire reference of Martinka, the Appellant does not believe it discloses what the Examiner suggests. The Martinka reference does not anticipate the pending claims because Martinka fails to disclose all of the claimed subject matter. For example, independent claim 1 recites "obtaining a sample set of pair-wise preferences among a subset of the alternatives" and "evaluating the candidate models using a fitness measure which is based on the sample set of pair-wise preferences." Independent claim 21 recites "using a model of preferences of a target audience" and "evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences." Independent claim 26 recites "evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise

preferences that are stored in memory." Independent claim 33 recites "generating the user's preferences for each pair of options in the plurality in response to the user's answers to the series of questions" and "evaluating a fitness measure for each of the plurality of values."

The Martinka reference merely discloses an apparatus for determining one or more solutions to a problem. *See* Martinka, col. 3, lines 41-42. The apparatus comprises code for traversing a path within a problem tree that includes multiple decision paths. *See* Martinka, col. 3, lines 42-50. The reference simply describes traversing the tree to test premises to determine the proper conclusion for a problem. *See* Martinka, Fig. 4; col. 5, lines 26-54. Clearly, the Martinka reference does not teach or suggest obtaining a sample set of pair-wise preferences among a subset of the alternatives. In addition, the Martinka reference does not disclose evaluating the models using a fitness measure that is based on the sample set of pair-wise preferences. Rather, the Martinka reference describes a compositional decision support reasoning system that utilizes *a root node*, which is "the first node for all decision paths in the given pursuit." *See* Martinka, col. 5, lines 26-31. In this manner, each node from the root node is processed to further verify the conclusion. *See* Martinka, col. 5, lines 31-54. Thus, the Martinka reference clearly does not disclose or suggest obtaining or utilizing pair-wise preferences, as recited in the present claims.

For at least the reasons set forth above, the Appellant respectfully submits that independent claims 1, 21, and 26 and the respective dependent claims are not anticipated by Martinka. Accordingly, the Appellant respectfully requests that the Board overrule the rejection of claims 1-24, 26-29, and 31 based upon the Martinka reference. Additionally, the Appellant respectfully requests that the Board allow claims 1-24, 26-29, and 31.

F. Ground of Rejection No. 6:

The Examiner rejected claims 25, 30, and 32 under 35 U.S.C. § 103(a) as being obvious over the Nomura reference in view of the Terano reference and in further view of alleged admissions by the Appellant.

i. Judicial precedent has clearly established a legal standard for a prima facie obviousness rejection.

The burden of establishing a *prima facie* case of obviousness falls on the Examiner. *Ex parte Wolters and Kuypers*, 214 U.S.P.Q. 735 (Bd. Pat. App. & Inter. 1979). Obviousness cannot be established by combining the teachings of the prior art to produce the claimed invention absent some teaching or suggestion supporting the combination. *ACS Hospital Systems, Inc. v. Montefiore Hospital*, 732 F.2d 1572, 1577, 221 U.S.P.Q. 929, 933 (Fed. Cir. 1984). Accordingly, to establish a *prima facie* case, the Examiner must not only show that the combination includes all of the claimed elements, but also a convincing line of reason as to why one of ordinary skill in the art would have found the claimed invention to have been obvious in light of the teachings of the references. *Ex parte Clapp*, 227 U.S.P.Q. 972 (Bd. Pat. App. & Inter. 1985). When prior art references require a selected combination to render obvious a subsequent invention, there must be some reason for the combination other than the hindsight gained from the invention itself, i.e., something in the prior art as a whole must suggest the desirability, and thus the obviousness, of making the combination. *Uniroyal Inc. v. Rudkin-Wiley Corp.*, 837 F.2d 1044, 5 U.S.P.Q.2d 1434 (Fed. Cir. 1988).

ii. The Examiner's rejection under 35 U.S.C. § 103 is improper because it fails to establish a prima facie case of obviousness.

Claim 25 depends from independent claim 21 and claims 30 and 32 depend from independent claim 26. Each of these claims is asserted to be patentable at least based upon their dependency from the independent claims 21 and 26. In the rejection, the Examiner

admitted that the Nomura and Terano references fail to expressly disclose the intended use for the decision making process. In an attempt to remedy the deficiencies, the Examiner relied upon a theory of inherency and alleged admissions by the Applicant in the "Background of the Invention" section of the present application.

The Examiner's inherency arguments and alleged admissions by the Applicant do not cure the deficiencies of the Nomura and Terano references, as discussed above. Therefore, claims 25, 30, and 32 are patentable by virtue of their dependency on independent claims 21 and 26. Further, the Examiner has not met the evidentiary burden of every aspect of the inherency argument. Indeed, the mere fact that a certain thing *may* result from a given set of circumstances is not sufficient. *See In re Robertson,* 169 F.3d 743, 49 U.S.P.Q.2d 1949 (Fed. Cir. 1999). In relying upon the theory of inherency, the Examiner must provide a basis in fact and/or technical reasoning to reasonably support the determination that the allegedly inherent characteristic *necessarily* flows from the teachings of the applied prior art. *Ex parte Levy,* 17 U.S.P.Q.2d 1461, 1464 (Bd. Pat. App. & Inter. 1990) (emphasis in original).

In light of the forgoing remarks, Appellant respectfully requests that the Board reverse the obviousness rejection in relation to claims 25, 30, and 32. Additionally, Appellant respectfully requests that the Board direct the Examiner to allow the instant claim.

Conclusion

Appellant respectfully submits that all pending claims are in condition for allowance. However, if the Examiner or Board wishes to resolve any other issues by way of a telephone conference, the Examiner or Board is kindly invited to contact the undersigned attorney at the telephone number indicated below.

Respectfully submitted,

Date: May 25, 2005

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8. APPENDIX OF CLAIMS ON APPEAL

Listing of Claims:

1. (Previously presented) A method for generating a model of preferences of a decision-maker, comprising the steps of:

identifying a set of alternatives to be presented to the decision-maker;

identifying a set of attributes associated with the alternatives;

characterizing the alternatives by obtaining a set of values for the attributes of each alternative;

obtaining a sample set of pair-wise preferences among a subset of the alternatives;

evolving the model of preferences that is stored in memory by iteratively generating a set of candidate models and evaluating the candidate models using a fitness measure which is based on the sample set of pair-wise preferences.

2. (Original) The method of claim 1, wherein the step of evolving includes the steps of:

constructing a population of the candidate models, each candidate model capable of expressing a modeled pair-wise preference between any two of the alternatives in response to the values for the attributes;

evaluating the candidate models from the population by examining the modeled pair-wise preferences of each candidate model over a subset of the alternatives and deriving a fitness measure which includes at least one criterion that penalizes the candidate models for disagreeing with the sample set of pair-wise preferences;

examining the population for one whose fitness measure meets a termination criterion.

3. (Original) The method of claim 2, wherein the criterion penalizes the candidate models based on a number of the sample set of pair-wise preferences that disagree with the modeled pair-wise preferences.

4. (Previously presented) The method of claim 2, wherein the step of obtaining a sample set of pair-wise preferences includes the steps of obtaining an indication of preference strength of the decision-maker such that the penalty for disagreeing with the sample set of pair-wise preferences is based on the indication of preference strength of the decision-maker.

5. (Original) The method of claim 2, wherein the candidate models each express the modeled pair-wise preferences by returning a number representing a utility value.

6. (Original) The method of claim 2, wherein the candidate models are each of a type from a set that includes a computer program type, a mathematical expression type, a neural network type, and a belief network type.

7. (Original) The method of claim 2, wherein the step of evolving further includes the step of constructing a new population from the population based on the fitness measures of the candidate models.

8. (Original) The method of claim 7, wherein the step of constructing a new population includes the steps of:

selecting a subset of the candidate models based on the fitness measures;

generating a set of new candidate models for the new population based on combining portions the selected subset of candidate models.

9. (Original) The method of claim 8, wherein the step of generating a set of new candidate models includes the step of combining portions the selected subset of candidate models using genetic operations.

10. (Original) The method of claim 1, wherein the step of obtaining the sample set of pair-wise preferences comprises the step of obtaining the sample set of pair-wise preferences comprises the step of obtaining the sample set of pair-wise preferences from the decision maker.

11. (Original) The method of claim 1, wherein the step of obtaining the sample set of pair-wise preferences comprises the step of obtaining the sample set of pair-wise preferences from a set of one or more other decision-makers.

12. (Original) The method of claim 11, wherein the step of obtaining the sample set of pair-wise preferences from the other decision-makers includes the step of obtaining a

common agreement among the other decision-makers for the sample set of pair-wise preferences.

13. (Previously presented) The method of claim 1, further comprising the step of:

identifying a set of characterization attributes associated with the decision-maker;

obtaining a set of values for the characterization attributes from a set of sample decision-makers from which the sample set of pair-wise preferences are obtained.

14. (Original) The method of claim 13, wherein the step of obtaining a set of values for the characterization attributes comprises the step of obtaining from the decision-maker a set of answers to a set of multiple choice questions.

15. (Original) The method of claim 13, wherein the step of evolving includes the steps of:

constructing a population of the candidate models, each candidate model capable of expressing a modeled pair-wise preference between any two of the alternatives in response to the values for the attributes and the values for the characterization attributes;

evaluating the candidate models from the population by examining the modeled pair-wise preferences of each candidate model over a subset of the alternatives and sample decision-makers and deriving a fitness measure which includes at least one criterion that penalizes the candidate models for disagreeing with the sample set of pair-wise preferences and corresponding values for the characterization attributes;

examining the population for one whose fitness measure meets a termination criterion.

16. (Original) The method of claim 1, wherein the step of obtaining a sample set of pair-wise preferences includes the steps of presenting the alternatives to the decision-maker and obtaining from the decision-maker a ranking of the alternatives.

17. (Original) The method of claim 1, wherein the steps of obtaining a sample set of pair-wise preferences comprises the step of presenting a textual description of each alternative.

18. (Original) The method of claim 1, wherein the step of identifying a set of alternatives comprises the step of selecting from a set of realized alternatives.

19. (Original) The method of claim 18, wherein the step of obtaining a sample set of pair-wise preferences comprises the step of obtaining from the decision-maker a relative preference between two successive realized alternatives experienced by the decision maker.

20. (Original) The method of claim 1, wherein the step of obtaining a sample set of pair-wise preferences comprises the step of presenting the decision-maker with the alternatives and observing a behavior of the decision-maker in response to the alternatives.

21. (Previously presented) A system for designing a presentation comprising means for selecting between a set of available alternatives each characterized by a set of observable attributes using a model of preferences of a target audience wherein the model that is stored in memory is evolved by iteratively generating a set of candidate models and evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences based upon responses from the target audience to a series of questions.

22. (Original) The system of a claim 21, wherein the presentation is customized for a specific member of the target audience.

23. (Original) The system of claim 22, wherein the specific member of the target audience is characterized by a set of values of a set of characterization parameters used with the candidate models.

24. (Original) The system of claim 21, wherein the presentation is designed to appeal to the target audience as a whole.

25. (Original) The system of claim 21, wherein the presentation is one of a set that includes a web page, a sequence of question, an advertisement, a direct-marketing solicitation, a set of one or more services, a set of one or more products, an establishment of a price of a product, an establishment of a price of a product, an establishment of a price of a

service, a shelf layout in a store, a display in a store, a sequence of actions, a sequence of steps used to diagnose a problem, a design of product, and a design of service.

26. (Previously presented) A device for deciding among a set of alternatives each characterized by a set of observable attributes comprising means for storing a preference model constructed by iteratively generating a set of candidate models and evaluating the candidate models using a fitness measure which is based on a sample set of pair-wise preferences that are stored in memory.

27. (Original) The device of claim 26, further comprising input means that enable a user to enter the observable attributes of the alternatives into the device.

28. (Original) The device of claim 27, wherein the input means enable the user to enter a set of values for a set of characterization parameters of the user that are used with candidate models.

29. (Original) The device of claim 26, further comprising means for obtaining a set of physical measurements associated with the observable attributes.

30. (Original) The device of claim 26, wherein the alternatives each represent one from a set that includes one or more services offered for sale and one or more products offered for sale.

31. (Original) The device of claim 26, wherein the alternatives include taking an action and not taking an action.

32. (Original) The device of claim 26, wherein each alternative represents a way of customizing a service.

33. (Previously presented) A method of customizing a computer program, the method comprising the acts of:

presenting a user with a plurality of pairs of customization options through a series of questions;

generating the user's preferences for each pair of options in the plurality in response to the user's answers to the series of questions;

assigning a plurality of values to each element of each pair of options in the plurality;

evaluating a fitness measure for each of the plurality of values;

selecting a subset from the plurality of values, wherein each member of the subset exceeds the fitness measure; and

combining the members of the subset using genetic operations to produce new values for each element of each pair of options in the plurality.

34. (Previously presented) The method of claim 33, wherein the customization options include the level of technical expertise required to operate the program.

35. (Previously presented) The method of claim 33, wherein the act of presenting the user with the plurality of pairs occurs over a computer network.

36. (Previously presented) The method of claim 33, wherein the genetic operations are chosen from the group consisting of mutation and cross-over.

37. (Previously presented) The method of claim 33, wherein the act of evaluating the fitness measure for each of a plurality of values further comprises the act of reducing each value if the value violates the generated user preference.

38. (Previously presented) The method of claim 1, wherein the step of obtaining a sample set of pair-wise preferences includes performing a survey of likely decision-makers.

9. **APPENDIX OF EVIDENCE**

Exhibit A. Terano et al., *Marketing Data Analysis Using Inductive Learning and Genetic Algorithms with Interactive-and Automated-Phases,* IEEE Int. Conf. Evolutionary Computation, 771 (1995).

Exhibit B. Wikipedia, Neural Network *at http:/en.wikipedia.org/wiki/ Neural_network*

Exhibit C. Wikipedia, Bayesian Network *at http:/en.wikipedia.org/wiki/ Belief_network*

Marketing Data Analysis Using Inductive Learning and Genetic Algorithms with Interactive- and Automated-Phases

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ABSTRACT

In this paper, to analyze questionnaire data on consumer goods for marketing decision making, we use inductive learning *and* genetic algorithms *with interactive and automated phases. The basic idea of the method is to integrate* inductive learning *to acquire decision trees or sets of decision rules and* genetic algorithms *to get the effective features to develop simple, easy-to-understand, and accurate knowledge from noisy data. The unique characteristics of the method is that the offspring (decision trees) are evaluated by both human-in-a-loop phase (*simulated breeding*) and automated* simple GA-Based *phase. The proposed method has been qualitatively and quantitatively validated by a case study on consumer product questionnaire data of 2,400 entries with 16 attributes.*

1. Introduction

Marketing decision makers must develop promotion strategies from noisy questionnaire data. Unlike popular learning-from-example methods, in such tasks, they must interpret the characteristics of the data without clear features of the data nor pre-determined evaluation criteria. AI-based inductive learning techniques for concept learning [Weiss *et al.* 1991] seem promising, however, they involve combinatorial feature selection problems. Feature selection is the problem in machine learning and statistical researches to choose a small subset of features that is necessary and sufficient to describe the target concept.

If we were able to have well-defined objective functions to be optimized, we could apply conventional GA techniques to choose appropriate features. In the task domain, it is not the case. We must interactively evaluate the resulting decision rules. To overcome the problem, we have developed an interactive method [1] to acquire efficient decision rules from questionnaire data using both *simulated breeding* and inductive learning techniques [Terano, *et al.* 1995]. *Simulated Breeding* is one of the GA-based techniques which subjectively or interactively evaluate the qualities of offspring generated by genetic operations with human-in-a-loop manner [Unemi 1994].

One of the issues to use SIBILE is that it requires knowledge intensive tasks to evaluate the offspring generated by inductive learning and genetic operations. In this paper, to improve the difficulty of SIBILE, we address a half-automated version of SIBILE: first, in the interactive phase, we subjectively evaluate decision trees or sets of decision rules to get the biases of features in the data as is used in [Terano, *et al.* 1995], then in the automated phase, using the biases, genetic operations are applied to develop offspring with 'effective' features. By the word 'effective', we mean the resulting decision trees or sets of rules are simple, accurate, and easy-to-understand.

This paper is organized as follows: In Section 2, we briefly introduce the concepts and features of simulated breeding and inductive learning. In Section 3, we explain the procedure of the proposed method. In Section 4, we demonstrate the results of experimental results conducted to validate the effectiveness of the method. In Section 5, we give some concluding remarks.

2. Simulated Breeding and Inductive Learning Techniques

The idea of simulated breeding is similar to the ones of *simulated evolution* or *interactive evolution* in computer graphics arts [Sims 1992]. In both methods, individuals judged by human experts to have some *efficient* features are allowed to breed their offspring. The judgments are subjectively or interactively done. In such cases where the evaluation function is not clearly defined, *simulated breeding* can improve breeds by selecting the parent for the

[1] SIBILE is a sibyl in old French, and stands for SImulated Breeding and Inductive Learning Environment.

next generation from among the pheno-types developed based on human preference.

The method most representative of inductive machine learning is ID3 [Quinlan 1986] which gives a decision tree or a set of decision rules as an output for the results of classification learning analysis on features and attribute-value pairs. Our research adopts C4.5 [Quinlan 1993] a noise tolerant successor of ID3. However, machine learning which attempts to incorporate all features in a decision tree is too complex [Menger 1989a]. Hence, selection of appropriate features becomes necessary. Various studies have been conducted to deal with the problem of interactions between features ([Kira *et al.* 1992], [Liu *et al.* 1992], [John *et al.*1994]). That is, feature selection intrinsically has combinatorial characteristics.

In the following sections, we will propose a method to solve the feature selection problem in inductive learning by both *simulated breeding* and a *GA-based* method. As a result, it is possible to develop a decision tree with comparatively smaller number of features and which incorporates human subjective evaluations.

3. Algorithm for Acquiring Decision Rules

The procedure of the proposed method is shown in Figure 1). Some additional descriptions are given in the following:

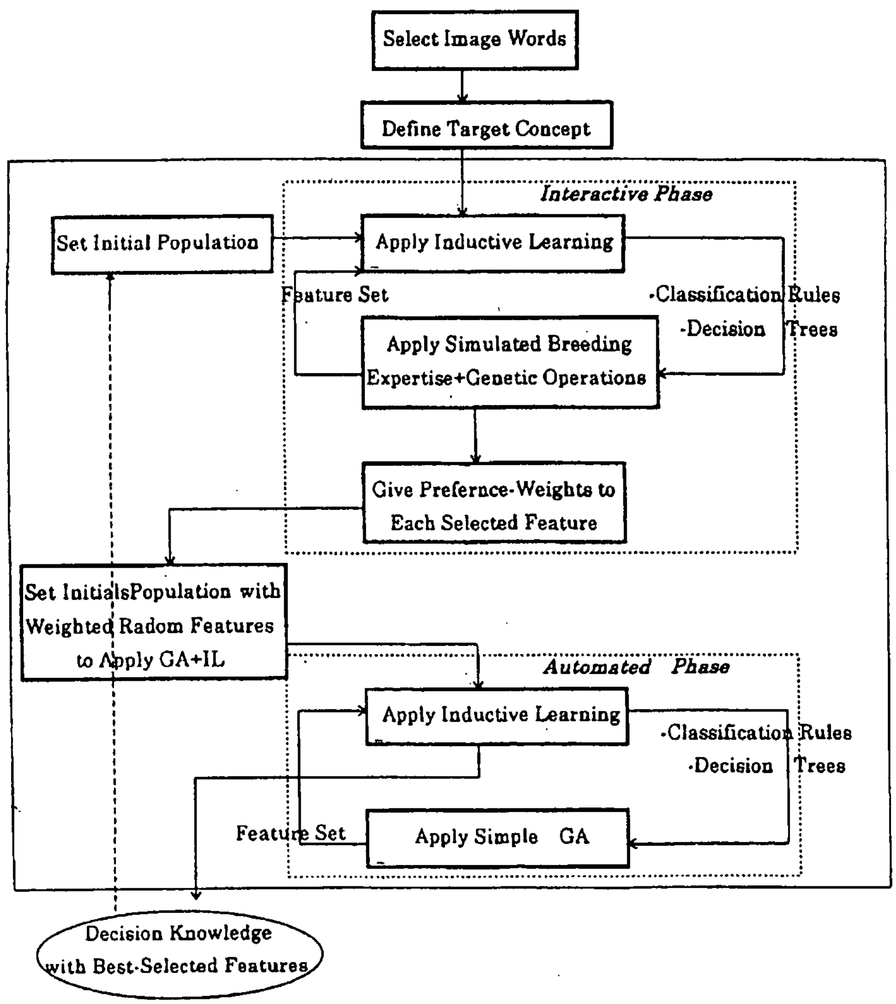

Fig. 1: SIBILE Algorithm with Interactive- and Automated-Phases

Step 1: Initialization

We generate the initial population, that is, we select m sets of individuals with less than or equal to l features. The m and l respectively represent the number of individuals and the length of their chromosomes. In our implementation, m and l are respectively set to 6 and 16. The chromosomes to represent the features are coded in binary strings, in which a '1' (respectively '0') means that a feature is (not) selected for inclusion in the inductive learning process.

Interactive Phase

Step 2: Apply Inductive Inferences

Inductive learning is applied to each of the m individuals with the selected features suggested as '1' in the chromosome. The data acquired from the questionnaire is aggregated, each of which has the corresponding features in it. Then the m sets of the data are processed by inductive learning programs. As stated earlier, we use C4.5 programs without modifications. As a result, m sets of decision trees with selected features or the corresponding set of decision rules are generated.

Step 3: Apply Simulated Breeding

In this step, a user or a domain expert must interact with the system. This is a highly knowledge-intensive task. Observing the forms of the decision trees, set of decision rules, and combinations of selected features, the domain expert subjectively and interactively evaluate the intermediate results to explain the characteristics of the predetermined n image words. He or she specifies two 'good' decision trees or 'good' rules generated from decision trees. The results will reflect the preference weight of each feature.

The trees selected are set as parents, and new product characteristics are determined by genetic operations. The corresponding chromosomes of the selected decision trees become parents for genetic operations. The selected two parents are preserved for the next generation. The rest m-2 offspring are replaced by the corresponding new m-2 offspring.

We apply modified uniform-crossover operations to them in order to get new sets of features to broaden the variety of offspring. The modified point is that the features are stochastically selected based on their preference weight values.

Step 4: Give Preference Weights to Each Selected Feature

Based on the judgment in Step 3, the preference weights are modified. If the user selects decision trees with good features, the preference weights of the corresponding features are equally increased. If the user selects some of the decision rules, the preference weights of the corresponding features of the rules are increased based on the user-specified preference values.

Step 5: Repeat the Steps

Steps 2 to 4 are repeated until an appropriate decision tree or set of decision rules is obtained. As are illustrated in [Dawkins 1986] and [Unemi 1994], the steps required to obtain the appropriate results are very small. In our experiments, it usually takes only less than 10 steps.

Automated Phase

Step 6: Set Initial Population with Weighted Random Features

Based on the preference weights interactive determined in Phase 1, the chromosomes or features are randomly selected to apply genetic operations. We generate the initial population, that is, we select m' sets of individuals with less than or equal to l features. The In our implementation, m' and l are respectively set to 12 and 16.

Step 7: Apply Inductive Learning

The procedure is same as Step 2.

Step 8: Apply Simple Genetic Algorithm

Each individual is evaluated by the following simple fitness function:

$$F(T) = \alpha A + \beta B + \gamma C + \delta D,$$

where, T means a corresponding decision tree, A = (number of tree nodes with all features)/(number of nodes of T), B = (number of rules to classify the data positive), C = (accuracy of T to classify the data positive), D = (accuracy of top three rules generated from T to classify the data positive). α, β, γ, and δ are parameters experimentally determined. In our experiments, we set $\alpha = 0.3$, $\beta = 1.5$, $\gamma = 28.0$, and $\delta = 0.2$.

We adopt the following genetic operations based on Simple GA in [Goldberg 1989]: Conventional one-point crossover, Mutation rate: 0.1, Generational replacement, and The best two parents preserved.

Step 9: Repeat the Steps

Steps 7 to 8 are repeated until an appropriate decision tree or set of decision rules is obtained. The steps required to obtain the appropriate results are approximately equal to 10-30. If the results are not

satisfactory when Automated Phase converges, return to Interactive Phase.

4. Experiments

To validate the effectiveness of the proposed method, we have carried out intensive experiments from a practical case study on consumer product questionnaire data. This section describes the experimental results.

4.1. Methods

Questionnaire data to investigate the features of new products in a manufacturing company was used as a case study of the proposed method. The experimental methods are summarized as follows.

- **Questionnaire used:**
  Questionnaire survey conducted with 2,300 respondents by a manufacturing company in 1993 regarding oral care products. The number of cases is usual for the questionnaire data in the task domain, and is large enough to apply the proposed method.
- **Domain Expert:**
  The resulting knowledge was evaluated by a domain expert who is concerned with marketing analysis on the task domain at the manufacturing company. She knows the basic principles of inductive learning programs, statistical techniques, and is able to understand the output results. Using the output forms of decision trees and corresponding rule sets from C4.5 programs, she has been required to interactively and subjectively evaluate the quality of the acquired knowledge from the viewpoints of simplicity, understandability, accuracy, reliability, plausibility, and applicability of the knowledge.
- **Experimental Methods and Implementation:**
  - 16 image words were selected to define product image. Respondents of the questionnaire evaluated how well each of the 16 image words fit the categories (*Fit*, *Moderate*, and *Does not Fit*, which will be respectively denoted as O, M, and X in the following sections, figures, and tables) of the toothpaste brand they mainly use.
  - 16 features words were selected for the evaluation. Respondents of the questionnaire evaluated whether they were *satisfied* or *not satisfied* with their toothpaste brand with regards to each of the 16 features. Therefore, the size of the search space is 2^{16}, which seems small to use Genetic Algorithms, however, it is enough large for using Simulated Breeding.
  - The experimental system was implemented on a Sun Sparc Station. The GA programs were written in C language, and C4.5 programs are used as an Inductive learning tool.

4.2. Results

This subsection presents the results of two experimental results for the selected images: *innovative* and *effective*. In the experiments, we have tried to acquire the knowledge to represent both of the two image words simultaneously.

Prior to the experiment, as an initial investigation, we applied C4.5 programs to the data with all 16 features. As a result, we have got a huge *pruned* decision tree with 113 nodes, which was impossible for even the experienced expert to correctly interpret. Further, using only Automated Phase of the algorithm in section 3, that is, using Simple GA, we have obtained a decision tree with 50-70 nodes. These results suggest that simple application of inductive learning and/or genetic algorithms do fail to acquire 'good' knowledge from the questionnaire data.

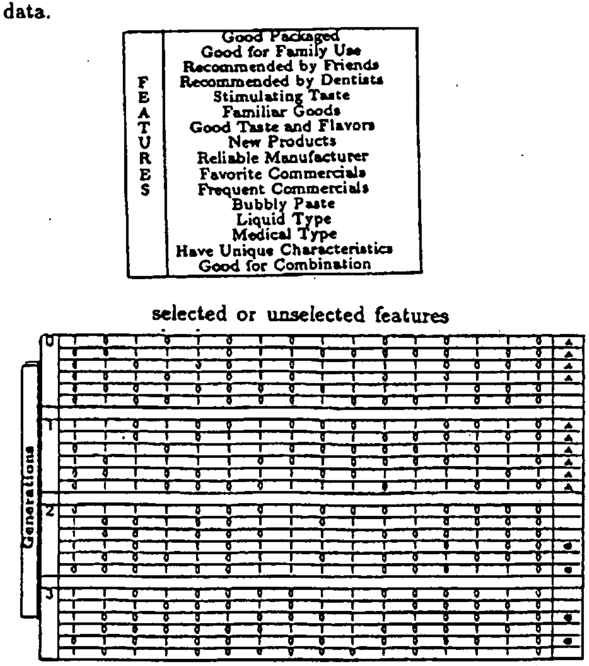

Fig. 2. Summary of Offspring of Interactive Phase

Figure 2 shows the results of the interactive phase of the experiment. The figure shows both the changes in the selected product characteristics (bit strings) and the size of corresponding decision trees.

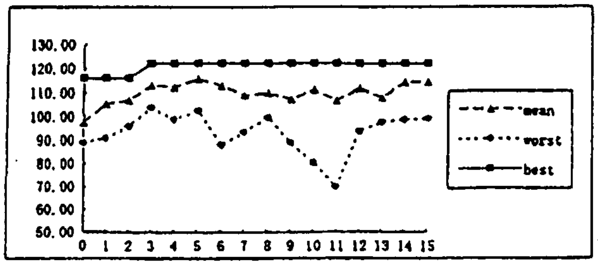

Fig. 3. Changes of Fitness Values in Automated Phase

The figure also shows the characteristics of offspring in each generation (Gen-x): '1' or '0' respectively mean selected or unselected features in each offspring. Black rectangles and circles respectively mean selected rules and decision trees to make offspring It took 3 generations in the phase. Figure 3 shows the changes of fitness functions in the automated phase.

Table 2: Accuracy Comparison of Direct Application of C4.5 and the Proposed Method

Methods	C4.5 all	C4.5, SB, GA
Features	16	5
Total Accuracy	57.3%	53.2%
Class O Accuracy	51.8%	42.8%
Class M Accuracy	81.2%	80.3%
Class X Accuracy	0.0%	0.0%

The final results of the decision tree and the corresponding rules are shown in Figure 4. The decision tree is represented in the form of standard outputs of C4.5 programs. The top left node means the top decision node. The lower decision nodes follow to down and right directions. Please refer to [Quinlan 1994] for the detail explanations. A human expert also judges that these acquired rules are easy-to-understand and simple enough to make practical marketing decisions.

Table 2 shows the accuracy comparison results of the tree with all features and the resulting tree generated by the experiment. About the further accuracy comparisons, we have demonstrated the superiotity of the proposed method in the other literature [Terano, *et al.* 1995], in which we have compared the proposed method with the ohter statistical methods: linear discrimination (LD) and automatic interaction detection (AID). The experimental results using *SAS* and *S* packages are also summarized in Table 3.

```
characteristic = YES: O (293.0/117.3)
characteristic = NO:
|   medicinal-type = YES: O (413.0/197.3)
|   medicinal-type = NO:
|   |   liquid = YES: O (32.0/16.3)
|   |   liquid = NO: M (1360.0/782.2)
```

```
Rule 6:
        medicinal-type = YES
        liquid = YES
        family-use = YES
        ->  class O  [33.7%]

Rule 10:
        characteristic = NO
        liquid = YES
        maker-value = YES
        family-use = YES
        ->  class O  [77.7%]

Rule 4:
        characteristic = YES
        liquid = NO
        family-use = YES
        ->  class O  [43.0%]

Rule 2:
        characteristic = YES
        maker-value = YES
        ->  class O  [42.2%]

Rule 7:
        medicinal-type = YES
        maker-value = YES
        ->  class O  [51.5%]

Rule 3:
        characteristic = YES
        maker-value = NO
        family-use = NO
        ->  class O  [33.3%]

Rule 9:
        medicinal-type = YES
        family-use = NO
        ->  class O  [37.0%]

Rule 13:
        liquid = YES
        maker-value = NO
        family-use = NO
        ->  class O  [33.9%]
```

Fig. 4. Resulting Decision Tree and Corresponding Rules

In our task domain, the total accuracy of the resulting rules and the accuracy for Class O are critical to get decision knowledge. Keep this in mind, the figure suggests that the proposed method shows the same level of accuracy compared with the tree with all features, in spite that the resulting tree is so simple and very easy to understand.

5. Concluding Remarks

In this paper, we have proposed a novel method to acquire efficient decision rules from questionnaire data by using inductive learning and genetic algorithms with interactive- and automated-phases. Using practical questionnaire data on marketing decision making, we have also shown the evolutional computation techniques such as simulated breeding can be applied to practical knowledge engineering problems.

Researches to integrate inductive learning and genetic algorithms are not quite novel in multistrategy learning literatures. For example,

Table 3: Accuracy Comparison of C4.5, LD, and AID

Methods	C4.5	LD	AID	C4.5	LD	C4.5	LD
Selected Features	All	All	All	Same 1.7.4	Same 1.7.4	Same 2.3.4	Same 2.3.4
Total Accuracy	57.3%	41.4%	56.0%	51.4%	40.6%	52.4%	33.9%
Class O Accuracy	51.8%	48.2%	61.3%	41.3%	37.2%	45.3%	50.4%
Class M Accuracy	81.2%	34.5%	69.4%	77.5%	43.8%	76.1%	8.2%
Class X Accuracy	0.0%	43.5%	0.9%	0.0%	40.0%	0.0%	66.5%

[Vafaie *et al.* 1994] has investigated automated feature selection for inductive learning program AQ with GA-based techniques. [Bala *et al.* 1994] has proposed another multistrategy approach to use GA to improve the performance of classification rules generated by AQ. The task domain is the classification of texture images with 18 features. The objective function of GA is defined based on the accuracy of the decision rules or classifiers. However, these researches differ from our problem in the aspect that we must determined the form of the objective functions to be evaluated in the interactive phase.

The pre-requisites of the proposed method are quite simple and the algorithm is easy to implement. Future directions of the work include to generalize SIBILE for a portable tool applicable to the other decision making problems and to specify SIBILE for efficient decision knowledge acquisition by improving the inductive learning techniques.

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Neural network

From Wikipedia, the free encyclopedia.

A **neural network** is an interconnected group of artificial or biological neurons. It is possible to differentiate between two major groups of neural networks:

- Biological neural networks, for example the human brain or parts thereof.
- Artificial neural networks originally referred to electrical, mechanical or computational simulations or models of biological neural networks. The field has expanded so that some applications do not clearly resemble any existing biological counterpart.

In modern usage the term most often refers to artificial neural networks, especially in computer science and related fields. There exist hybrids, incorporating biological neurons as part of electronic circuits, so there is not always a clear delineation.

In general, a neural network is composed of a group of connected neurons. A single neuron can be connected to any other neurons so that the overall structure of the network can be very complex. Artificial intelligence and cognitive modeling try to simulate some properties of neural networks. Approaching human learning and memory is the main interest in these models. These artificial neural networks are advantageous, especially in in pattern recognition and classification tasks. They have found an application in the control of processes in the chemical industry, speech recognition, optical character recognition and adaptive software such as software agents (e.g. in computer games) and autonomous robots.

In some comparisons between the brain and computers the following calculation is made: There are billions of neurons in the human brain, estimates suggest roughly about $2 * 10^{12}$ neurons with individual differences. The relaxation time of these neurons is about 10 ms, this could amount to a processing speed of 100 Hz. The whole brain could therefore have a processing speed of roughly $2 * 10^{14}$ logical operations per second. These considerations are however very speculative. To compare, a PowerPC 970 at a frequency of 3 GHz and 64 bits (PowerPC) corresponds to $2 * 10^{11}$ logical operations per second in the case of the PowerPC. However, this comparison is very speculative, since the working of biological neural networks is not well understood. Perhaps the most fundamental difference between brain and computer is that today's computers operate sequentially (or occasionally with a small amount of parallelism possibly through such technology as Hyper-threading and SIMD instructions like MMX and SSE2), while human brains are massively parallel. Further, concerning differences of artificial neural networks and biological neural networks, while a computer works centralized with a processor at its core, the question of whether the brain works centralized or decentralized (distributed) is not resolved. Given Turing's model of computation, the Turing machine (which shows that any computation that can be performed by a parallel computer can be done by a sequential computer), this is likely to be a functional, not fundamental, distinction.

The parallel distributed processing in mid-1980s became popular under the name connectionism. In early 1950s Friedrich Hayek was one of the first to posit the idea of spontaneous order in the brain arising out of decentralized networks of simple units (neurons). A design issue in cognitive modeling, also relating to neural networks, is additionally a decision between holistic and atomism, or (more concrete) modular in structure.

See also

- Cognitive architecture
- Biologically-inspired computing
- parallel distributed processing

- Biological cybernetics

External links

- Connectionism at MindDict (*http://artsci.wustl.edu/~philos/MindDict/connectionism.html*)

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Categories: Cybernetics | Neural networks | Artificial intelligence

Bayesian network

From Wikipedia, the free encyclopedia.
(Redirected from Belief network)

C

A **Bayesian network** or **Bayesian belief network** is a directed acyclic graph of nodes repr
arcs representing dependence relations among the variables. If there is an arc from node A t
we say that A is a **parent** of B. If a node has a known value, it is said to be an **evidence** node. A node can represent any kind of variable, be it an observed measurement, a parameter, a latent variable, or a hypothesis. Nodes are not restricted to representing random variables; this is what is "Bayesian" about a Bayesian network.

A Bayesian network is a representation of the joint distribution over all the variables represented by nodes in the graph. Let the variables be $X(1), \ldots, X(n)$. Let $parents(A)$ be the parents of the node A. Then the joint distribution for $X(1)$ through $X(n)$ is represented as the product of the probability distributions $p(X(i) \mid parents(X(i)))$ for i from 1 to n. If X has no parents, its probability distribution is said to be **unconditional**, otherwise it is **conditional**.

Questions about dependence among variables can be answered by studying the graph alone. It can be shown that the graphical notion called d-separation corresponds to the notion of **conditional independence**: if nodes X and Y are d-separated (given specified evidence nodes), then variables X and Y are independent given the evidence variables.

In order to carry out numerical calculations, it is necessary to further specify for each node X the probability distribution for X conditional on its parents. The distribution of X given its parents may have any form. However, it is common to work with discrete or Gaussian distributions, since that simplifies calculations.

The goal of inference is typically to find the conditional distribution of a subset of the variables, conditional on known values for some other subset (the **evidence**), and integrating over any other variables. Thus a Bayesian network can be considered a mechanism for automatically constructing extensions of Bayes' theorem to more complex problems.

Bayesian networks are used for modelling knowledge in gene regulatory networks, medicine, engineering, text analysis, image processing, and decision support systems.

Learning the structure of a Bayesian network is a very important part of machine learning. Given the information that the data is being generated by a Bayesian network and that all the variables are visible in every iteration, the following methods are used to learn the structure of the acyclic graph and the conditional probability table associated with it. The elements of a structure finding algorithm are a scoring function and a search strategy. An exhaustive search returning back a structure that maximizes the score is one implementation which is superexponential in the number of variables. A local search algorithm makes incremental changes aimed at improving the score of the structure. A global search algorithm like Markov chain Monte Carlo does not get trapped in local minima. Friedman et. al. talk about using mutual information between variables and finding a structure that maximizes this. They do this by restricting the parent candidate set to k nodes and exhaustively searching therein.

See also

- graphical model
- machine learning

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